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Research Article

Impact of Improved Forage Technology Adoption on Dairy Productivity and Household Income: A Propensity Score Matching Estimation in Northern Ethiopia

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Adoption of improved forage technologies remains to be one of a promising strategy to boost dairy productivity and enhance household income in many developing countries. However, there are limited rigorous impact evaluation studies on the contributions of such technologies on smallholder dairy productivity and household welfare. This paper examined the impact of improved forage technologies use on smallholder dairy productivity and farm household income in Northern Ethiopia. In this study, a cross-sectional survey design and a multistage stratified sampling procedure were employed. Primary data for the study were obtained from a random sample of 319 rural households, 128 of which are improved forage technology users and the rest are nonusers. The research employed the propensity score matching (PSM) procedure to determine the causal relationship between adoption of improved forage technologies and changes in milk yield and farm household income. Results from PSM revealed that households using improved forage technologies have increased the household milk yield (productivity) by 29.32% and farm income (welfare) by 19.56%. Higher milk yield and annual farm income were compared to those households not using such technologies. Our findings highlight the importance of promoting multiple improved forage technologies among rural smallholder's dairy producers. Considering this potential, it is suggested that improved forage technology generation, dissemination, and adoption interventions be strengthened for optimum milk production and to attain optimum income under the smallholder farmers' dairy production system. Moreover, the linkage among research, extension, universities, and farmers needs to be enhanced through facilitating a multistakeholder's innovation platform.

1. Introduction

Ethiopia is a growing country in Sub-Saharan Africa with a huge livestock potential, rated first among African countries and ninth overall. However, milk production is remained very low [1]. The livestock production subsector has a huge contribution to the national economy and generating income to farmers, creating job opportunities, ensuring food security, providing services, contributing to asset, social, cultural and environmental values, and maintain livelihoods [2]. The subsector consists largely of smallholder farming systems with multiple uses and contributes around 16.5% of the national GDP, 35.6% of agricultural GDP, 15% of export revenues, and 30% of agricultural employment. [3].

Despite its high population, the country's livestock productivity is very low. Besides animal health problems, lack of adequate quantity, and quality feed is a key impediment to low livestock productivity. The utilization of improved feed is restricted (0.31%) in rural areas of Ethiopia [3]. The country is endowed with various feed resources having different feed use share, which encompassed natural pasture grazing (54.59 %), followed by crop residue (31.60 %), hay (6.85%), agro-industrial byproducts (1.53%), and-others like animal byproducts and vegetable and fruit wastes

(5.11%) [3]. However, because these resources are in short supply and of poor quality, animal feed shortages continue to be the most significant barrier to output in both the lowlands and the highlands.

The dairy subsector in Ethiopia has not been effectively developed and promoted, and milk output in the country has fallen far short of expectations. The dairy herd's productivity is low, with an average milk yield of 1.3 L–1.54 L per day in indigenous cattle and 10 L per day in crossbred cattle during mean lactation duration of 180–210 days [4, 5]. When compared to the average for the geographic region and the world, this is reflected in the country's low per capita milk consumption. This per capita milk and meat consumption is 16 liters per year and 13.9 kilograms per year, respectively, falling short of African, and thus worldwide per capita milk and meat consumption of 27 kilograms per year and 100 kilograms per year, respectively [6].

Ethiopia's dairy output is limited by a number of interconnected challenges classified as technical and nontechnical restrictions. Nontechnical constraints include the policy environment, socioeconomic problems, and institutional issues. Land availability, financing availability, and other incentives, as well as extension services, infrastructural setups, and overall coordination, are all influenced by these factors. This, in turn, has a direct or indirect impact on the production of dairy products. Ethiopian cattle policies, according to Defege et al. [7], are inefficient in terms of finance, extension, marketing, and infrastructure.

On the other hand, the key technical obstacles limiting dairy production are insufficient feed and nutrition, the presence of numerous diseases and poor health services, and the genetic make-up of indigenous breeds. For biological and economic reasons, the most important barrier is a lack of feed supplies, both in terms of quantity and quality. From the biological aspect, nutrition is often responsible for roughly two-thirds of the cost of increasing dairy output. Feed expenses account for around 60 to 70% of overall dairy production costs, meaning that the dairy enterprise's viability is determined by the type of feed and feeding system used [8]. Dairy cattle productivity is sometimes limited by inadequate nutrition caused by poor quality feeds and inconsistent feed supply, especially in resource-constrained smallholder systems in the country.

Hence, the low productivity of the livestock sector is a result of several limiting factors among which feed is the major one [9, 10]. In spite of serious problems of feed shortage and large number of livestock in the Ethiopian highlands, adoption and popularization of forage crops is very poor [10].

It is believed to be that the availability of improved fodder particularly green feed, as one of the major elements affecting dairy output, with the other factors remaining constant, has a good impact on dairy production performance and body condition [11]. During the dry and wet seasons, nonadopters' milk yields were estimated to be 1.3 litres/day/cow and 2.4 litres/day/cow, respectively. In the dry season, forage adopters' milk outputs were predicted to be 3 liters/day/cow, and in the rainy season, 6 liters/day/cow (wet season). This shows that fodder adopters produce higher milk yields than nonadopters with the same cow breed, which could be due to a variety of variables, including the usage of improved fodder. When there is a dearth of green feed at this time of the year, the days open are longer and the calving interval is longer [12]. Feed shortages, silent estrus, and heat sensing challenges, according to the same scientists, may have all had a role in the extended days open. Similarly, poor heat detection, fewer accesses to AI services, and poor feeding practices could all contribute to a longer calving interval [13].

Many improved forage crops have been tested and selected for the highlands. Some of them have been demonstrated to farmers, but their adoption is still very slow [14, 15]. Oats is the only crop, which is widely cultivated both for human food and as forage for livestock in the central highlands of Ethiopia, especially around Selale, Sheno, Debreberhan, and Arsi areas. Oats is becoming very popular in many areas because it performs well on waterlogged and frost problematic areas and on soils with poor soil fertility which is less suitable for other food crops [16, 17]. Different governmental and nongovernmental organization has been engaged in the development and promotion of different improved forage technologies in Ethiopia in general and in Debre Libanos district in particular. The major improved forage crops adopted in the study area were oat, vetch, elephant grass, *Sesbania*, Rhodes grass, tree lucerne, desho grass, alfalfa and fodder beet.

Several studies have been conducted to evaluate the rate of livestock feed technology adoption and to understand the major reasons for the low adoption among smallholder farmers Gebremedhin [18–20]. However, the majority of previous research have mainly centered on the rate of adoption and factors associated with adoption of technologies. Moreover, most of these studies generally assumed widespread use of technologies, which might not hold true for improved feed technologies. Apart from quantifying and describing the situations, there is scanty empirical literature on the impact and performance of improved forage technology adoption being developed, disseminated and/or scaled-up by different agricultural research centers, NGOs, and universities. Therefore, the current study scientifically investigated the impact of improved forage technologies on smallholder dairy productivity and farm household income in Northern Ethiopia.

2. Methodology

2.1. Description of the Study Area. The study was conducted in three selected kebeles of Debre Libanose Wereda, North Shewa Zone of Oromia RegionalState. Debre Libanose is one of the thirteen weredas of North Shewa zone of Oromia Region. Geographically, the Wereda is located between latitudes of 09° 43′ 30″°N longitudes and 38° 51′ 0″°E latitudes (Figure 1). It is found at about 104 kilometer from Addis Ababa and 14 km from Fiche Town, the capital of North Shewa Zone, in the Oromia Regional State. It is located in the altitude ranges between 1500 and 2635 meters above sea level. The study area is characterized by diverse landscape, flora, fauna, and habitat types. The area has extremely steep slopes leading up to a strip of plateau. It has bimodal rainfall pattern ranging from 800 mm

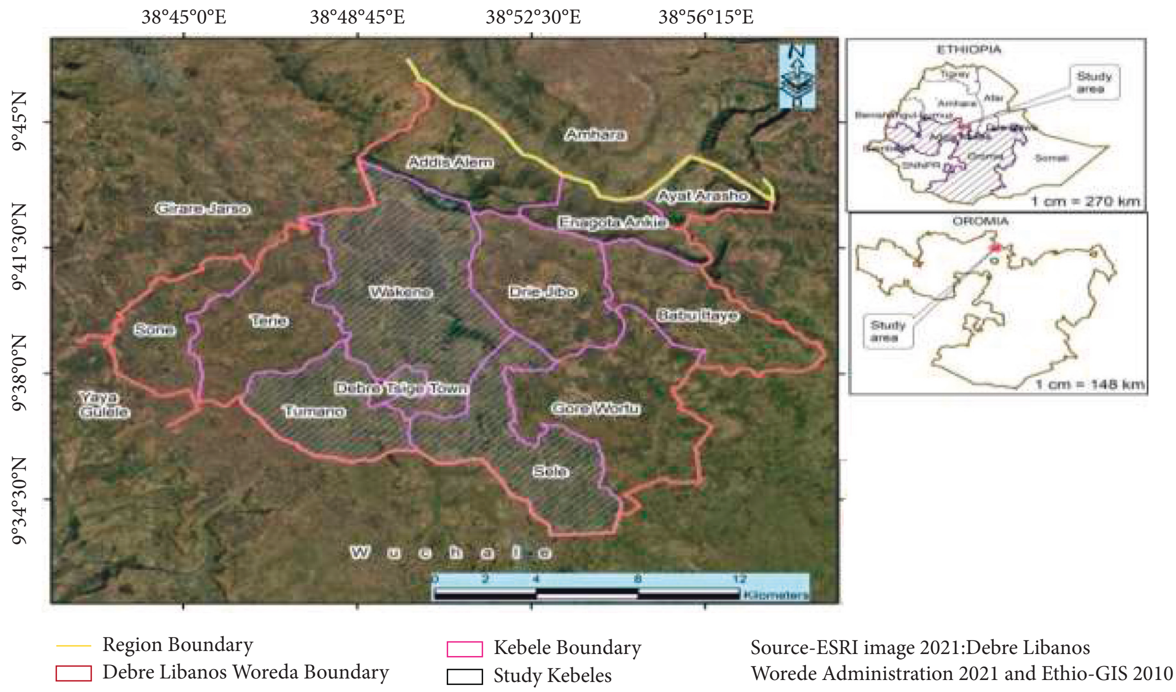

Figure 1: Map of the study area (source: ESRI image 2021; Debre Libanos Wereda Administration 2021 and Ethio-GIS 2015).

to 1200 mm with five months of rain (May-September). The dry *P* is from December to March. The annual average maximum and minimum temperature of the study area is 23°C and 150°C, respectively.

There are about 81,796 head of cattle, 8480 goats, 24923 sheep, 10200 equines, and 80,305 poultry in the Debre Libanose Wereda. All of these livestock types are primarily raised by smallholder farmers in intense, semi-intensive, and extensive production systems. The district is divided into 11 administrative PAs and 15,000 liters of milk is collected from Debre Tsige Town (DWLFO, 2014). The total area of the wereda is about 27,500 s, of which 23,960 (87.1%), 2,547 (9.3%), 833 (3.0%), and 166 (0.6%) hectares are agriculture, grazing land, forest land, and other use, respectively, (North Shewa Zone Culture Tourism Office/April, 2017).

The main economic activities in these study areas are mixed crop-livestock farming, which is practiced by smallholder farmers. Agriculture accounts for 54.3%, pastoral farming 36%, handwork products 5%, and other accounting 0.7% (North Shewa Zone Culture Tourism Office/April 2017). The area is regarded as a high potential crop-livestock belt, with dairy activities playing a key role in farmers' livelihoods. Given the area's potential and the economic importance of dairy production to the local community, governments and nongovernmental aid organizations have made several initiatives to boost dairy productivity. This area also has better access to livestock development services (both governmental and nongovernmental) and milk markets than other rural locations. Due to the aforementioned reasons and the economic ability of the peasant's smallholder dairy production with crossbred dairy cattle is a prevalent practice in the area (North Shewa Zone Culture Tourism Office/April, 2017).

Debre Libanose Wereda was selected as a study area based on the following reasons: the dairy potential of the wereda to fill information gaps of previous studies and identify location-based empirical evidence about the impact and determinants of smallholder farmers' improved forage technologies adoption (North Shewa Zone Culture Tourism Office/April, 2017). *(Wereda, in this case is equivalent to a district).

2.2. Sampling Technique and Sample Size Determination. A multistage stratified random sampling procedure was employed in this specific study. In the first stage, the study area (Debre Libanose district) was selected purposively based on its improved forage production potential and number of dairy technology availability and practiced in the area. Second, three kebeles were randomly selected from the wereda among potential improved forage producer. Third, within the selected kebeles, the respondent households were stratified into two groups: forage technology adopters and nonadopters. Adopters were households who are cultivating and continue using improved forage crop for feeding their livestock. At the end, simple random sampling was applied to select the sample household farmers.

From the total of 1895 households, 319 farm household heads were selected randomly, using probability proportionate to size and out of which 128 were adopters and 191 nonadopters farm households participated in the process as depicted in Table 1. The total sample size ($n = 319$) was determined by using Kothari's (2004) sample size determination formula. A simplified formula provided by Kothari's (2004) employed to determine the required sample size at 95% confidence level, degree of variability = 0.5 and the level of precision = 5% (0.05).

Table 1: Sample size and distribution by sample kebeles.

S/N	Kebele's name	Total households in each Kebele	Adopter households		Nonadopter households		Total sample size
			Total	Sample	Total	Sample	
1	Sele	420	120	30	300	44	71
2	Tumano	480	150	37	330	52	81
3	Wakene	995	285	61	710	95	167
Total		1895		128		191	319

$$n = \frac{Z^2 pq}{d^2}, \quad (1)$$

where n = the desire sample size; Z = standard normal variable at the required level of confidence; P = the proportion in the target population estimated to have characteristics being measured; d = the level of tactical significance set; and $q = 1-p$.

2.3. Methods of Data Collection. In this study, both qualitative and quantitative data type of primary and secondary source were utilized. Secondary data were collected through reviewing published and unpublished documents and Internet as well. This information was used to evaluate the existing works and compare the study with the previous studies. Primary data were collected using two-survey procedures, formal and informal surveys. In informal survey: key informant interview, focus group discussion, and transect walk were done using respondent and development agents. Checklists were developed to conduct key informant interviews and focus group discussions. A total of five focus group discussions and 15 key informant interviews were made. Then, the draft structured questionnaire was prepared. In the formal survey: data were collected using a structured questionnaire by applying face-to-face interview with household heads. Moreover, a pretest survey was conducted prior to the actual survey work to test data collection instruments, to assess the clarity of the questions for respondents, estimate the time required to finalize the interview, and revises the questionnaire accordingly.

For this purpose, 25 households were randomly selected for a pretest survey before the actual survey. Then, the survey questionnaire was tailored to the local conditions. Finally, well-trained enumerators who have good experience in the household survey work were employed to gather the data required for this study.

2.4. Methods of Data Analysis. For this particular study, both descriptive statistics and econometric models were employed to analyze the data collected from primary sources.

2.4.1. Statistical Analysis

(1) Propensity Score Matching (PSM). It employed propensity score matching (PSM) approaches that select, match, and compare forage producing households and without improved forage technologies with similar characteristics. This is used to measure the impact of forage technology adoption on smallholder dairy productivity and household livelihoods. Match treated (adopters) and untreated (nonadopters) observations on the estimated probability of being treated (propensity score). Allows not only for mean matching, but also for balancing the distribution of observed characteristics between treatment and control groups. It is used to match each adopter with an identical nonadopter and then measure the average difference in the outcome variable between the adopter and the nonadopter.

(2) Estimation of Propensity Score. The first one is concerning the model used for the estimation of variable, and the second is about the variable to be included in the model. In this case application of a logit model was used in estimating the logit model. Since this study had binary treatment adopter and nonadopter of improved forage technologies, the dependent variable was a dummy variable (improved forage technology adopter in this case). Adopters took a value of one if the households adopt improved dairy technologies and zero otherwise [21].

$$p_i = \frac{e^{Z_i}}{1 + e^{Z_i}}, \quad (2)$$

where P_i is the probability of adoption of improved forage technology.

$$Z_i = \beta_0 + \sum \beta_i X_i + U_i, \quad (3)$$

where β_0 = intercept, β_0 = regression coefficient to be estimated, X_i = variable, and U_i =disturbance term. The probability that a household belongs to the nonadopter's group is

$$1 - p_i = \frac{1}{1 + e^{Z_i}}. \quad (4)$$

The odds ratio can be written as

$$\frac{p_i}{1 - p_i} - \frac{1 + e^{Z_i}}{1 + e^{-Z_i}} = e^{Z_i}. \quad (5)$$

Therefore, to estimate average impact of improved forage technology adoption on dairy productivity and household livelihoods,

$$E[Y_1 - Y_0 \mid D = 1] = E[Y_1 \mid D = 1] - E[Y_0 \mid D = 1], \quad (6)$$

where Y is yield per liter (say, in liter or in birr) and D takes the value 1 for adopters (treatment group) and 0 for nonadopters (control group). Thus, the outcome of interest is the average difference in Y_1 and Y_0. However, since one farmer may only be in one condition at a time, this matching exercise tries to estimate only $E[Y_0|D = 1]$, which is the counterfactual or unobservable situation. At a time (either in the treatment group or the control group), in our case, this means, trying to estimate the impact of being an adopter on yield per liter for those farmers who are actually in the control group.

For experimental data in which the farmers are randomly assigned to the treatment and control groups, it would have been possible to estimate the average treatment effect (ATE) as

$$ATE = E[Y_1 \mid D = 1] - E[Y_0 \mid D = 0]. \quad (7)$$

However, this study is based solely on observational data and does not include any experimental data. Hence, instead of ATE, the issue of interest for this study is the average treatment effect on the treated (ATT), based on Rosenbaum and Rubin (1983) to solve the selection bias by estimating the following equation:

$$\% \; E[Y_1 - Y_0 \mid Z, D = 1] = E[Y_0 \mid Z, D = 1] - E[Y_0 \mid Z, D = 1], \quad (8)$$

where Z is a set of factors that influence a farmer's adoption status. If Z determines the likelihood of becoming an adopter, it is possible to create a control group of nonadaptors with Z values identical to adopters (the treatment group). As a result of (3), the average treatment effect on the treated (ATT) can be calculated as follows:

$$\begin{aligned} \mathrm{ATT} = E[Y_1 - Y_0|P(Z), D = 1] &= E[Y_1|P, (Z), D = 1] \\ &\quad - E[Y_0|P(Z), D = 0], \end{aligned} \quad (9)$$

where $P(Z)$ is the probability of selection conditional on Z or it is the propensity score (pscore) which is $P(Z) \equiv P_r$ $(D = 1 \mid Z)$.

As a result, the matching is done in two steps with Stata's psmatch2. First, the propensity scores (P-scores) are calculated using Stata's "pscore" command. The pscores are the conditional probabilities that a given farmer adopting the improved forage technology. Calculating the propensity score is critical since it is difficult to do the matching on each explanatory variable when there are many covariates. The primary purpose of the propensity score estimation is to balance the observed distribution of covariates between the two groups. Matching test was also performed after matching to check whether or not the differences in covariates in the two groups in the matched sample have been eliminated. Finally, good matching quality was achieved. In the second stage, the average treatment effect on the treated (ATT) was estimated using psmatch2. Robustness of the ATT found by using psmatch2 was also checked by running matching algorithms such as the nearest neighbor (NN), kernel, and radius matching techniques. psmatch2 is selected due to the fact that it estimates both propensity score and ATT by itself:

(1) Model specification for matching algorithm

(i) Kernel matching
The model is applied to pool data from both treated and untreated subjects, an estimated probability of participation for each subject.

$$\begin{aligned} E y_i^{1-} y_i^0 &= /p(x_i) T_i = 1) \\ &= \frac{1}{n^1} \sum_{t=(T_1=1)}^{n^1} \left[y_i^1(x_i) - w_j(p(x_i)) y_j^0 \right]. \end{aligned} \quad (10)$$

Associate to the outcome y_i of treated unit i. The matched outcome given by kernel-weighted average of the outcome of all nontreated units, where the weight given to nontreated unit j is in proportion to the closeness between i and j.

(ii) Nearest neighbor model specification
C is the set of control (nonadopters) unit, denoted by $C(i)$ the set of control units matched to treat unit i with an estimated value of the propensity score p_i. The nearest neighbor matching is set.

$$C(i) = \min j \left\| p_i - p_j \right\|. \quad (11)$$

(iii) Radius matching
If the control units with estimated propensity scores falling within a radius r from pi are matched to the treated unit i, then

$$C(i) = \left\{ p_j \mid \left\| p_i - p_j \right\| < r \right\}. \quad (12)$$

Each treated unit is matched only with the control unit whose propensity score falls into a predefined neighborhood of the propensity score of the treated unit.

2.5. Conceptual Framework. The adoption and diffusion of agricultural technology varies a lot from place to place. In general, the variations in adoption patterns proceed from the presence of disparity in agroecology, institutional, and social factors. Moreover, farmer's adoption behavior, especially in low-income countries, is influenced by a special set of socioeconomic, demographic, technical, institutional, and biophysical factors. Farmer's decision to adopt new technologies can even be influenced by factors associated with their objectives and constraints. These factors include farmer's resource endowments as measured by size of family labors, farm size, and livestock ownership, farmers' socioeconomic circumstance (age and formal education), and institutional web available for inputs [41]. In many developing countries, it has become apparent that generating new technology alone has not provided solution to assist poor farmers increase agricultural productivity and achieve higher standards of living. In spite of the efforts of the national and international development organizations, the matter of technology adoption, and hence, low agricultural productivity remains a serious concern [41]. During this study, efforts were made to work out adoption and intensity of improved forage

Table 2: Description, measurement, and expected sign of hypothesized variables.

Variable name	Measurement unit	Expected sign
	Dependent variable	
Adoption of improved forage technologies	1 if household used improved varieties and 0 otherwise	
	Outcome variables	
Income from sales of milk	Birr	
Milk yield	Liter	
	Independent variable	
Age of the household	Age of the household head (in years)	−/+ve
Sex of a household	0 for female and 1 for male	−Ve
Educational level	Year	+ve
Total farm size	Land holding (ha)	+ve
Annual income	Household annual income in Ethiopia birr	+ve
Improved cattle owned	Livestock ownership in TLU	+ve
Extension contact	Twice a month, once a month, and once in a season	+ve
Attend filed day	1 if household participate in field day and 0 otherwise	+ve
Attend in training	1 if household attend in training and 0 otherwise	+ve
Market distance	Distances of market in kilometer	−Ve

among smallholder farmer's demographic, socioeconomic, institutional, and biophysical characteristics.

Despite many years of effort on forage research and extension activities, the adoption and utilization of improved forages by farmers are very low. Generally, several factors affect adoption of improved forage technologies. For example [22], examined determinants of forage adoption and production niches among smallholder farmers in Kenya using the binary logistic model. Their findings indicated that access to formal education of the household head, experience in livestock farming, and land ownership influenced adoption of improved forage technologies positively and significantly. Likewise, [18] studied determinates of improved forage technologies adoption among smallholder farmers in the northeast highland of Ethiopia using a double hurdle model. The model result revealed that access to extension services, age of the sample household-head, farm size, livestock ownership, and labor available had a positive and significant effect on the adoption of forage technologies, implying that improving the resource endowment of farmers would boost agricultural production.

On the other hand, [23] analyzed determinates of improved forage technologies in Doyogena District of Kembata Tembaro Zone, in southern nations, nationalities regional state, and Ethiopia the using logistic regression model. The model result mentioned that access to formal education, training, and number of dairy cattle owned affected positively the household choice to take part in adoption of improved forages in the district, while access to communal land, access to market point, and farmers training center negatively affected the probability.

It is explained that the abovementioned factors influence the probability of adoption and use of improved forage technology by several factors of demographic, socioeconomic, institution, and biophysical variables. Accordingly, explanatory variables were defined and hypothesized to evaluate the impact of improved forage technologies adoption based on the information extracted from the theoretical literature review of previous works (Table 2).

3. Results and Discussion

3.1. Descriptive Statistics Results. In this study, a total of ten explanatory variables were identified, and out of these variables eight of them revealed significant association with the adoption and intensity of use of improved forage technology. Variables such as age, education, TLU, farm size, and field day are continuous, whereas age of household, training, filed day, and extension contact are dummy variables that show statistically significance at 1%, 5%, and 10% significant level with the adoption decision. However, market distance and off-farm income had not statistically significant relation with the adoption decision. The summary of the overall descriptive results of this study is presented in Tables 3 and 4.

3.2. Demographic and Socioeconomic Characteristics of Respondents. This subsection described the household characteristics that explain the information on demographic and socioeconomic characteristics such as age of the household, sex of the household, educational level, family size, farm land size, income from off-farm activities, access to credit, access to training, attendance in filed day, market distance, extension contact, tropical livestock unit, and input access which is assumed that either positively or negatively influence the adoption decision of improved forage technology adoption. Some demographics and socioeconomic characteristics of the sample population, with comparison of the adopters and non-dopters, are presented (Tables 3 and 4) for continuous and categorical variables, respectively. Out of the total 319 respondents, 40% were adopters, while the remaining 60%, were nonadopters.

As indicated in Table 3, the mean age of the adopters is 42.61, while it is 45.5 years for nonadopters. The mean age of the adopters is less than the mean age of the nonadopters in technology adoption. Thus, the mean difference was found to have statistically significant with $P = 0.039$ value, this implies that there was significant difference on the mean age

Table 3: Demographic and socioeconomic characteristics for continuous variables (t-test).

Types of variables	Adopter ($N = 192$)		Nonadopter ($N = 128$)		Combined		t-value	P value
	Mean	Std	Mean	Std	Mean	Std		
Age (number)	42.61	11.3	45.5	12.87	44.34	12.33	2.064	0.039**
Education (year)	1.16	0.88	0.59	0.755	0.815	0.85	−6.1707	0.0000***
TLU (number)	8.65	3.89	6.54	3.42	7.39	3.76	−5.1040	0.0000***
Farm size (hectare)	2.61	1.24	1.90	1.12	2.19	1.22	−5.3363	0.0000***
Market distance (walking distance in minutes)	34.24	24.92	32.57	23.77	33.24	24.21	−0.6038	0.5464

The symbols *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively. Source: authors' analysis using primary data (2021).

Table 4: Demographic and socioeconomic characteristics for binary variables (X^2-test).

Variables	Categories	Adopter ($N = 192$)		Nonadopter ($N = 128$)		Total value		X^2-value	P value
		Count	%	Count	%	Count	%		
Sex	Male	115	42	158	58	274	85.89	2.75	0.097*
	Female	13	29	32	71	45	14.11		
Training	Yes	58	79.45	15	20.55	73	22.88	60.938	0.000***
	No	70	28.46	176	71.54	246	77.12		
Field day	Yes	64	90.14	7	9.86	71	22.26	95.092	0.000***
	No	64	25.81	184	74.19	248	77.74		
Extension contact	Yes	123	67.96	58	32.04	181	56.74	134.88	0.000***
	No	5	3.26	133	96.38	138	43.26		
Income from off-farm	Yes	34	46.58	39	53.42	73	22.88	1.6392	0.200
	No	94	38.21	152	61.79	246	77.12		

The symbols *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively. Source: authors' analysis using primary data (2021).

of the household head in the two groups at 5% level of significant. This suggests that young people tend to be more adopters of new technologies than the old aged people.

Education is one of the other most important factors that determine the decision to accept new agricultural technology. This is due to the fact that literate household heads are more likely to see the benefits of technology and contribute to improved innovation and invention. The results further depicted that the year of education of the adopters is 1.16, while the figure is 0.59 for the nonadopter households,. Furthermore, the mean difference was found to be statistically significant. The calculated probability implies that there was significant mean difference in education status of the adopter and nonadopter households ($P = 0.001$). This finding is in conformity with the work of Biru [24], which indicated that literate farmers are better in adopting improved technologies than the illiterates.

Farm animals (TLU) have an important role in the rural livelihood. They are the source of draught power, to supplement protein needs, as prestige, cash, animal dung for organic fertilizer and fuel, means of transport, and as a hedge against hard times in general. The types of livestock found in the study area were cattle, sheep, and goat, equine, and chicken. Mixed farming system (i.e., integrated crop and livestock production) is the main agricultural activity in the study area. Accordingly, the draught power is taken as a major source of production in the study area. Beside this, the effect of livestock ownership was found to have a significant effect on adoption of improved forage technology. The average livestock ownership for adopters and nonadopters was found to be 8.65 and 6.54, respectively. The P value implies that there is a significant mean difference between the two groups ($P = 0.001$). Accordingly, the adopter household has more livestock owners than nonadopters. This finding is in line with the study by Bedassa [19], which reported that as livestock ownership increases, adoption and intensity of adoption was expected to increase and correlate positively.

On the other hand, farm size is a more decisive socioeconomic variable that is vital for agricultural practice and livelihood improvement. In comparison with improved forage adoption, the average cultivated land size of the adopter households was 2.61 ha and the corresponding figure for the nonadopters was 1.90 ha (Table 3). The mean difference of the two groups was found to have statically significant ($P = 0.001$). The result is consistent with [25] finding that there is a direct relationship between the farm size of land held by farm households and forage technologies adoption. Therefore, farmers with large land size can adopt new agricultural technologies than smallholders and land size would initiate to adopt improved forage technologies.

Among the dummy variables, the sex distribution of sample households, from the total sample household, 85.89% of them were male and 14.11% of them were female headed. With regard to the sample respondents improved forage technology adoption status, 89.84% of improved forage technology practitioners were male household head while the rest 10.16% were female. From the nonadopter's household side, around 83.25% and 16.75% of the total respondents were male and female, respectively. On an average, the chi-square test of sex distribution between the adopters and nonadopters was found to be statistically significant ($P = 0.097$) and this shows that, there is strong significant relationship between sex of adopters and nonadopters in the improved forage technology adoption. This finding is in conformity with the work of Astatkie and Taha [26, 27] which stated that due to many sociocultural values and norms, male has freedom of mobility and participation in different extension programs and consequently has greater access to information. Therefore, it is hypothesized that male farmers are more likely to adopt package.

On the other hand, participation in training, in terms of technology specific training, the result of descriptive analysis indicated those 22.88% sampled household have attended the training while the rest 77.12% have not attended the training. Training can improve the knowhow of farmers on technology. The more farmers involve in training, the more they make a decision to use a technology. It means that, around 54.69% of adopter group and 92.15% of nonadopters responded that they were not attended training. In the revers, 45.3% of adopters and 7.85% nonadopter group that they were attended training. The chi-square test confirmed that the association between the attained training and improved forage adoption was significant ($P = 0.001$). The finding is in line with the findings of Abebe et al. [28] who reported those farmers with access to trainings have better chance to adopt improved forage.

Farmer`s participation in field day and demonstration activity indicated that 22.26% of sample household have participated, while the rest 77.74% of household have not participated in field day and demonstration activities. It means that, around 50% of adopter group and 96.34% of nonadopters households responded that they were not participated in field day and demonstration activities, whereas 50% of adopters and 3.66% nonadopter group have participated. This implies that farmers were interested to learn from field day activities. The chi-square test indicated that there was a significant association between attending field day and improved forage technology adoption ($P = 0.001$).

Extension contact believed to enhance awareness among smallholder farmers about new agricultural technologies and farming activities. Mainly, Kebele extension agents and district supervisors capacitate smallholder farmers in various ways. For example, participation in demonstration day and providing technical assistance provides improved varieties of seeds and practical training to innovative farmers. The survey result revealed that out of the total sample household farmers, 56.74% of the sample household have contact with extension agents, while the remaining 43.26% of the household have no contact. It means that, around 3.91% of adopter group and 69.63% of nonadopter households responded that they were not contacted with extension agents, whereas 96.1% of adopters and 30.4% of nonadopter group have contacted with extension agent. The chi-square test confirmed that the association between extension contact and improved forage technology adoption was significant ($P = 0.001$) and suggesting that extension contact is important in highly influencing farmers' decision to adopt improved forage technology. This finding is in conformity with the work of Beshir [18].

Regarding adopter's participation on off-farm income activities from the total sample households, it was found to be 22.88% for adopter households that was engaged in off-farm income activity and the rest 77.12% of the households not engaged in off-farm activities, while from nonadopters, 20.42% are engaged in the off-farm activities and 79.58% are not a part of it. Conversely, from adopters, 26.56% are engaged in the off-farm activities and 73.44% are not a part of it. However, the chi-square result indicated that ($P = 0.200$) there was no variation between adopters and nonadopters in participation on off-farm income activities in improved forage technology.

3.3. Econometric Model Estimation Results

3.3.1. Impacts of Improved Forage Technology Adoption on Milk Yield and Farm Income. This section describes econometric analysis which was followed to spot the impact of improved forage production technologies adoption on milk yield and farm income. The section was analyzed that the estimation of propensity scores, choosing matching algorithm, and calculating average treatment effect (ATT) on the treated.

Propensity score matching (PSM) is employed to match adopter and nonadopter so as to form reasonable counterfactual [29]. Propensity score construct a statistical comparison between treated individual with control individual based on similarities in all observable characteristics except the treatments so as to compute the difference within the outcome variable. This implies that the average treatment effect of the technology adoption is calculated as the mean difference in outcomes across the two groups. [29]. According to Khandker et al. [30], the PSM effect validity depends on conditional independence and sizable common support across the adopter and nonadopter sample household.

In the first step, the logit model is used to estimate the propensity scores for matching purpose [31]. Accordingly, in this study ten explanatory variables were identified and used to fulfill the criteria of the balancing propensity among those variables, seven of them were found to be significant variable that determine the decision of adopting improved forage technologies and use of improved forage technologies positively and significantly, while the rest three variables were not significant in explaining the variation in the dependent variable.

In the first step, the logit model is employed to estimate the propensity scores for matching purpose [31]. Accordingly, in this study ten explanatory variables were identified and used to fulfill the criteria of the balancing propensity. The next step after balancing the predicted probability values, from the binary estimation, matching was done by using the matching algorithm. A matching algorithm is selected based on the data at hand in order to select the control group who are matched with the treated group based on the covariant which needs to be controlled.

In general, this section presents the result of logistic regression, in the first step in the propensity score matching is to

Table 5: Propensity score estimation.

Variables	Odds ratio	St. Err.	Z	P value
Sex of the household head	0.751164	0.4446473	−0.48	0.629
Age of the household head	1.030092	0.0167485	1.82	0.068**
Education status	1.610852	0.3580113	2.15	0.032**
Farm size	−0.973829	0.1896029	−0.14	0.892
Market distance	1.016346	0.0065929	2.50	0.012**
Access to extension	16.9979	9.304402	5.18	0.000***
Training	2.73146	1.194584	2.30	0.022**
Field day demonstration	16.3326	9.266719	4.92	0.000***
Improved cattle owned	1.54224	0.1279083	5.22	0.000***
Farm income	1.00003	2.99e − 06	1.13	0.259
_Cons	0.000172	0.000294	−5.08	0.000
Sample size (N) = 319 pseudo R^2 = 0.4296 LR chi2 (13) = 184.62				
Prob > chi2 = 0.0000 log likelihood = 122.544				

The symbols *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively. Source: authors' analysis using primary data (2021).

estimate the matching improved forage technology adopter household with nonadopters. The logistic regression results in Table 5 demonstrated that there are different variables that determine household decision in improved forage technologies practice at different statistically significant levels.

In this study, ten selected explanatory variables were hypothesized that determine household's participation in improved forage technologies adoption. Among those variables, seven of them were found to be significant variables that determine the adoption of households in the decision of adopting improved forage technologies and use of improved forage technologies positively while the rest three variables were not significant in explaining the variation in the dependent variable.

The output of binary logistic regression (Table 5), revealed the age of the household head, education of the household head, distance to wereda market, and access to extension services. Access to training, field day demonstration, improved cattle holding were the effect the household's probability of adoption and use of improved forage technologies positively and statistically significant at $P < 0.01$ and $P < 0.0.5$ significant level, respectively.

Our finding pertaining to the effect of age of household were found to positively affect improved forage technology adoption and this result is consistent with the findings reported by Admassie et al. [32]. Similarly, education of household head was found to significantly affect improved forage technology adoption. This finding also in line with the findings of Bassa [23]. Another factor that hindered households' probability to adopt technologies adoption is the market distance effect. In this study, distance from the market was found to have a significant and positive effect. Contrast to hypothesized, as a negative determinant variable, the result of regression analysis showed positive correlation. Different studies result indicated that distance from the market has significant and negative effect on the farmers' decision to adopt agricultural technology [32, 33]. Access to extension services happened to have positive and significant effect on the probability of household's decision to adopt improved forage technology. Moreover, this finding is in line with Teklay et al. [34–36] and Abebe et al. [28] who found a positive and significant effect of number of extension contacts on the decision to adopt improved forage.

Training: accordingly, as the model result indicates, participation in training has positively and significantly affected the adoption of improved forage technology. The effect of training for this study is consistent with the findings of Abebe et al. [28, 35], which indicate that the training was positively related to adoption of improved forage technology. Field day: the logit result indicates that the probability of improved forage adoption was positively and significantly affected by field participation at 1% ($P = 0.00$) probability level. Similar results were reported by Kedir et al. [35, 37–40]. These studies indicated that demonstration and dissemination of information through field day and demonstration activities might facilitate adoption of improved varieties. Finally, improved cattle owned in TLU was found that it is positively associated with the probability of adoption of improved forage technology. The result of the logit estimation revealed that the adopter households with improved cattle have showed high probability of adoption of improved forage than the counterpart household with the local cattle only in the study area. The reason for this positive effect was that improved forage and improved cattle are much intertwined, and hence, its availability could increase the area under cultivation and the probability of adoption. Therefore, it is expected that the number of improved cattle owned would have positive correlation on the adoption improved forage technologies and this finding is in conformity with Bedassa [19].

As described in Table 5, the pseudo-R^2 value is large and the value is (0.4296) indicated that the adoption of the household is fairly random. According to Caliendo et al. [21], after matching, there should be a systematic difference in the distribution of covariates between adopter and nonadopter groups. The next step after balancing the predicted probability values, from the binary estimation, matching was done by using the matching algorithm. A matching algorithm is selected based on the data at hand in order to select the control group who are matched with the treated group based on the covariant which needs to be controlled.

3.3.2. Propensity Score Histogram. The propensity score matching (PSM) is to match each participant based on an identical common characteristic with nonparticipants. Thus, the distribution helps to identify the impact of forage technology adoption on milk yield and farm income. In line with this, the density distribution of propensity scores for adopters and nonadopters is shown in Figure 2, the bottom-half of each graph shows the propensity score distribution of nontreated (nonadopters), while the upper-half refers to treated individuals. The y-axis indicated the frequency of the propensity score distribution.

As shown within the above figure, treated on support indicated the farmers within the adoption group who found an acceptable match, whereas untreated indicate

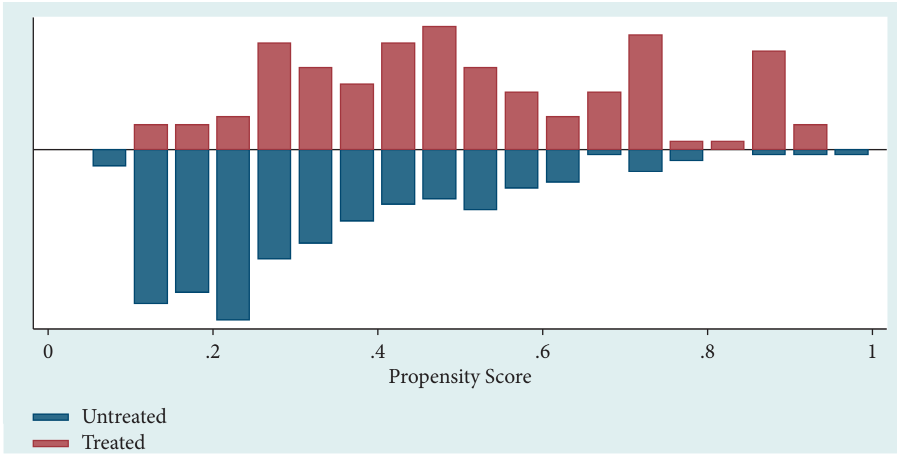

Figure 2: Propensity score distribution and common support region between the treated and untreated.

Table 6: Testing of covariate balance using the propensity score (evaluation of quality of match).

Covariates	Samples	Mean		% of bias	% reduction bias	P value
		Treated	Controlled			
Sex of the household head	Unmatched	0.84375	0.80105	11.2		0.073*
	Matched	0.83621	0.56034	2.1	56.0	0.169
Age of the household head	Unmatched	42.609	45.503	−3.9		0.040**
	Matched	42.069	39.595	10.4	14.5	0.193
Educational status	Unmatched	1.1563	0.58639	69.4		0.000***
	Matched	1.1121	1.3448	−18.3	59.2	0.143
Farm size	Unmatched	2.2252	1.7718	50.6		0.000***
	Matched	2.1701	2.3677	−2.0	56.4	0.127
Market distance	Unmatched	34.242	32.571	6.9		0.546
	Matched	33.845	25.474	4.4	40.8	0.672
Access to extension	Unmatched	0.9375	0.4293	130.1		0.000***
	Matched	0.9310	0.9482	−4.4	96.6	0.583
Training	Unmatched	1.3672	1.5445	−6.1		0.002***
	Matched	1.3793	1.3017	15.8	56.2	0.214
Filed day demonstration	Unmatched	0.5	0.03665	122.2		0.000***
	Matched	0.4652	0.3607	17.3	77.7	0.111
Improved cattle owned	Unmatched	6.2344	3.0262	116.3		0.000***
	Matched	5.6724	6.6379	−5.0	69.9	0.454
Farm income	Unmatched	1.0e + 05	54517	71.6		0.000***
	Matched	93714	1.1e + 05	−17.8	75.2	0.189

(Figures in bold shows significant covariates)

The symbols *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively. Source: computed from own survey (2021).

nonadopters.The results of the covariate balancing test to check the hypothesis that both groups have similar distributions in covariates after matching are presented in (Table 6). The result revealed the covariates mean, the percentage bias, and also the P value difference in the mean before and after matching.

Choosing the best performing matching algorithm was employed to check the balancing of covariate by comparing before and after matching algorithm significance difference using the selected matching algorithm.

The above (Table 6 and Figure 3) results revealed that the mean standardized bias difference in before matching is in a range of 6.9%–130.1% in absolute value and P value in the same table shows 80% of chosen variables exhibited a statistically significant difference at before matching, whereas after matching the standardize bias/standard error difference of explanatory variables lied between 2.1% and 17.3%. If the value of this statistics exceeds 20, the covariate is assumed to be unbalanced [29]. Accordingly, in all cases, it had been evident that sample differences within the unmatched data significantly exceeded those in the samples of matched cases. Hence, the method of matching created a high degree of covariate balance between the treatment and control samples that were ready to be used in the estimation procedure. The below figure indicated that the standardized % bias across covariates (unmatched with matched covariates).

Similarly, the joint significant test in Table 7 below revealed that the value of pseudo R^2 was very low, it had been

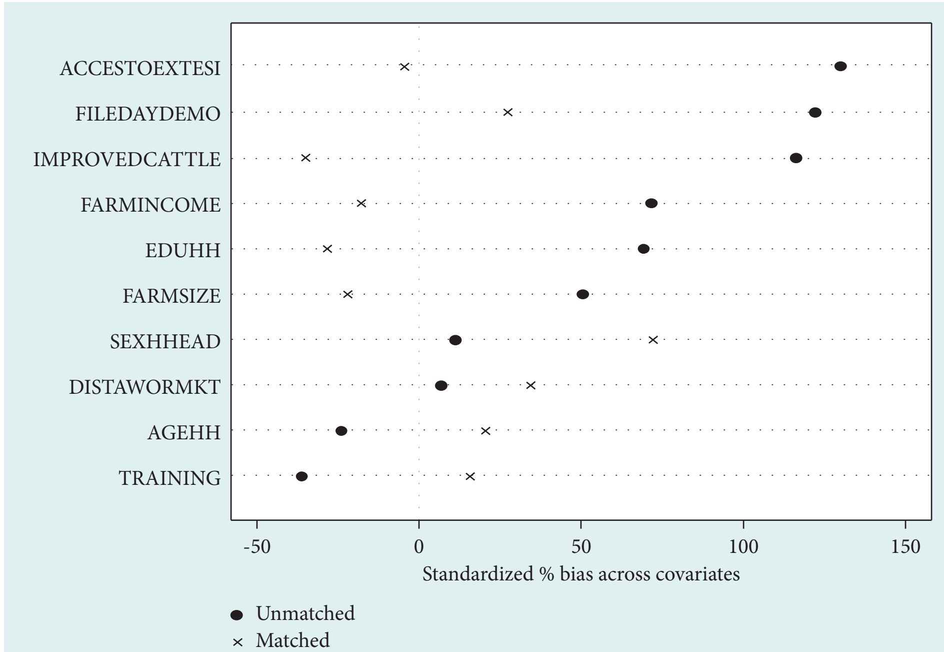

Figure 3: Unmatched and matched standardized % bias across covariates.

Table 7: Post estimation of PSM.

Sample	Ps R^2	Lr chi2	$P >$ chi2	Mean bias	Med bias	B	R
Unmatched	0.511	219.47	0.000	63.8	60.0	212.8	29
Matched	0.001	52.70	0.874	4.3	3.7	24.0	0

Source: authors' analysis using primary data (2021).

Table 8: Performance criteria of matching algorithms.

Outcome variables	Matched algorithms (kind of matching)	Matched samples		ATT (impact)	Bootstrapped std. Err.	t-test
		Adopters	Nonadopters			
Milk yield	Kernel-based matching (KBM)	128	191	5701.92	1287.26	4.41***
	Nearest neighbor matching (NNM)	128	191	5701.92	1072.99	3.99***
	Radius matching (RM)	128	191	5701.92	1429.81	4.10***
Milk income	Kernel-based matching (KBM)	128	191	26050.79	5803.38	4.88***
	Nearest neighbor matching (NNM)	128	191	26050.79	6718.919	4.86***
	Radius matching (RM)	128	191	26050.79	4808.817	4.26***

Source: authors' analysis using primary data (2021) *** denotes statistically significant at $P < 0.01$.

minimized to 0.001 and the t-test was not significant. The low value of pseudo R^2 indicated that the improved forage technology adopter and nonadopter households had the same distribution in the covariates after matching. The mean bias is additionally minimized from 63.8 to 4.3. Beta is also minimized to 24.0 which is less than 25 so, these also gives as guarantee that the matching process created a good balance between participants and nonparticipants based on the included covariates. Therefore, estimation of the average treatment effect on the treated (ATT) was preceded.

3.4. Estimating Treatment Effects (ATT). To check the robustness of the result, different matching methods such as kernel-based matching (KBM), nearest neighbor matching (NNM), and radius matching (RM) were computed for both outcome variables, namely, milk yield and farm income (milk income) as indicated in Table 8 and the impact of the adoption is shown by the difference in ATT.

In general, all the three matching methods revealed that, adopters of improved forage technologies have generated significantly higher output (milk yield litter/annum and milk income birr/annum) compared to the nonadopter households, with a statistically significant difference at $P = 0.001$ level. This implies that, better milk production and much better farm income were gained by adopting improved forage technology, which in turn encourages adoption of the improved forage technologies. Based on the study result, all

Table 9: Estimation of ATT for milk yield (lit/annum).

Outcome variable	Sample	Treated	Controlled	Difference	S.E.	T-stat
Yield (milk)	Unmatched	8264.75	2562.827	5701.92277	1033.4196	5.00
	ATT	7760.02	3518.793	4241.23276	1139.5171	2.49

Source: authors' analysis using primary data (2021).

Table 10: Estimation of regression adjustment for milk yield (lit/annum).

	Milk yield	Coef.	Robust Std. Err.	z	$P>\|z\|$
ATET	Adoption (adopter vs. nonadopter)	4308.87	1539.803	2.80	0.005
POmean	Adoption nonadopter	3955.88	814.2236	4.86	0.000

Source: authors' analysis using primary data (2021).

Table 11: Estimation of ATT for farm income (birr/annum).

Outcome variable	Sample	Treated	Control	Difference	S.E.	T-stat
Farm income (milk sale birr/annum)	Unmatched	41042.9922	14992.19	26050.798	4966.261	5.25
	ATT	41970.1466	23474.26	18495.879	9175.714	2.02

Source: authors' analysis using primary data (2021).

Table 12: Estimation of regression adjustment for farm income (birr/annum).

	Farm income (milk sale)	Coef.	Robust std. Err.	z	$P>\|z\|$
ATET adoption	(adopter vs. nonadopter)	15191.56	7515.397	2.02	0.043
POmean	Adoption Nonadopter	25851.43	5136.166	5.03	0.000

Source: authors' analysis using primary data (2021).

of the below result (Table 8) suggested that the matching algorithm chosen relatively for this study. Therefore, it is possible to proceed to estimate the average treatment effect on the treated (ATT) for the sample households.

3.5. The Impact of Adoption of Improved Forage Technologies on Milk Yield. The estimated average treatment effect (ATT) results of sample households found by using psmatch2 revealed that adoption of improved forage technologies generated positive and statistically significant milk yield differences between treated and controlled group, measured in milk production (lit/annum). Table 9 shows that, the average treatment effect on the treated (ATT) of milk yield of adopters and nonadopters for the production year of 2012/13 E.C had been 4241.23 milk yield (liters/annum) difference over the untreated is statistically significant at 5% ($t=2.49$; $P=0.05$) probability level. In terms of the average yield (milk) of the treated and the nontreated, the psmatch2 result showed that, treated groups harvested average milk yield of 7760.02 (liters/annum), while the nontreated/control/groups harvested average milk yield of 3518.79 (liters/annum) which is also statistically significance at 5% ($t=2.49$; $P=0.05$) probability level. This suggests that improved forage technology adoption has increased the household milk yield by 29.32%. Therefore, intensification of improved forage technology should be given due emphasis in order to increase yields and improve dairy farmers' livelihoods. This confirms that, improved forage technologies is worth adopting. Adopter participants in the focus group discussion/FGD/indicated that, the cultivation/production of improved forage crops is very useful in a way that it is improving fertility of their soil, increasing dairy production, and productivity, while also increasing their income and improving their livelihood.

To supplement the impact study in addition to the PSM method, regression adjustment has been employed and the estimated average treatment effect on treated (ATET) results of sample households found by using regression adjustment revealed that adoption of improved forage technologies generated positive and statistically significant milk yield differences between treated and controlled group, measured in milk production (lit/annum) as depicted in Table 10.

3.6. The Impact of Adoption of Improved Forage Technologies on Farm Income. The estimated average treatment effect on treated (ATT) of the sample smallholder households showed that, adoption of improved forage technology has strong positive significant effect on farm income too, measured in birr per annum. The ATT result found by using psmatch2 showed that adoption of improved forage technologies has created on average positive farm income differences between adopters and nonadopters. Table 11 shows that, the average treatment effect on the treated (ATT) of farm income obtained from milk sale has 18,495.879 ETB difference over the controls. Similarly, just like the yield advantage seen above, the treated (adopters) are beneficiaries of economic advantage due to the adoption of improved forage technologies and their difference is statistically significant at 5% ($t = 2.02$; $P = 0.05$) probability level. In line with average annual income of the treated and the nontreated, the psmatch2 result showed that, treated groups earned average annual income of 41,970.146 ETB, from the sale of milk commodity as adopters, while the control groups earned average annual income of 23,474.267 ETB, from the sale of milk which is statistically significant at 5% ($t = 2.02$; $P = 0.05$) probability level. And this implies that improved forage technology adoption has increased the household farm income (income from milk sale) by 19.56%. It can be seen that both the yield and income result favored the treated groups who are adopters of the improved forage technologies.

Hence, the study shows that, the nonadopters lose on two grounds: (i) adopters have better yield and income advantage over the nonadopters by adopting the improved forage technologies (as indicated in yield ATT section). Therefore, huge effort is needed from the research and extension service in availing and diffusing new and improved forage crop varieties and technologies in order to generate additional income for smallholder dairy producers.

Similarly, for farm income generated from sale of milk regression adjustment has been also employed to substantiate the PSM impact study method and the estimated average treatment effect on treated (ATET) results of sample households found by using regression adjustment revealed that adoption of improved forage technologies generated positive and statistically significant farm income differences between treated and controlled group, measured in (Birr/annum) as depicted in Table 12.

4. Conclusions and Implication

In this study, we evaluated the causal effect of using improved forage technologies on dairy productivity and farm household income using 319 randomly selected households in Northern Ethiopia. The study employed the PSM estimation procedure. Through collecting data specifically for the purpose of impact evaluation and implementing rigorous evaluation methods, the key findings of the study showed that smallholder farm households using improved forage technologies developed, disseminated, and/or scaled-up by different agricultural research centers, universities and different NGOs had a statistically significance on milk yield and household income compared to those not using these technologies. More specifically, the result of PSM revealed that improved forage technologies adoption has increased the household milk yield (productivity) of adopters of household by 29.32% and farm income (welfare) by 19.56%. Higher annual milk yield and farm income per household are compared to nonadopter households. The ATT result of improved forage technologies adoption on milk yield and farm income also resulted significant on all algorithms used.

The results of this study revealed that adopters have better yield and income advantage over the nonadopters by adopting the improved forage technologies. This implies that introducing and disseminating of appropriate improved forage technologies to smallholder farmers could improve dairy productivity and income of smallholder. This could help smallholder dairy producers to attain optimum income and maximum margin for its livelihood. Thus, huge effort is needed from key stakeholders like agricultural research centers, NGOs, universities, and extension service in availing and disseminating new improved forage crop varieties and technologies to smallholder dairy farmers in the district and to the region at large. So that, smallholder dairy farmers would increase their productivity using the technologies which in turn raise farmers' income.

Abbreviations

ATE: Average treatment effect
ATET: Estimated average treatment effect on treated
CCT: Contingency coefficient test
CSA: Central statistical agency
GDP: Gross domestic product
FGD: Focus group discussion
KBM: Kernel-based matching
KI: Key informant
RM: Radius matching
ILRI: International livestock research institute
NNM: Nearest neighbor matching
NN: Nearest neighbor
PSM: Propensity score matching
VIF: Variance inflation factor.

Data Availability

The data analyzed for this study are available from the first author on reasonable request.

Ethical Approval

To care for both the study participants and the researchers, ethical clearance letters were obtained from Addis Ababa University and Holetta Agricultural Research Centers. Clients were informed that they had the ability to terminate or decline participation in the study. As a result, all participants in the study, including survey households, enumerators, supervisors, and key informants, were fully informed of the study's purpose. Until the end of the study, they were approached in a friendly manner.

Consent

During the survey, official letters were written for the district and peasant associations, and each respondent provided informed verbal agreement, and confidentiality was maintained by assigning codes to each respondent rather than recording their identity.

Disclosure

This manuscript is extracted from the author's thesis work part which entitled "Improved forage technologies adoption and its impact on smallholder dairy productivity: the case of

Debre Libanose, Wereda, Oromia Region, Ethiopia." "Wereda" is an administration unit equivalent to district, whilst "Kebele" is the lowest administration unit in Ethiopia.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

The first author designed the study, analyzed the data, and wrote the paper. The co-author supervised data collection and analyzed qualitative data. Finally, all authors read and approved the final manuscript.

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